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A novel statistically tracked particle swarm optimization method for automatic generation control

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Abstract Particle swarm optimization (PSO) is one of the popular stochastic optimization based on swarm intelligence algorithm. This simple and promising algorithm has applications in many research fields. In PSO, each particle can adjust its 'flying' according to its own flying experience and its companions' flying experience. This paper proposes a new PSO variant, called the statistically tracked PSO, which uses group statistical characteristics to update the velocity of the particle after certain iterations, thus avoiding local minima and helping particles to explore global optimum with an improved convergence. The performance of the proposed algorithm is tested on a deregulated automatic generation control problem in power systems and encouraging results are obtained.

Keywords Statistically tracked particle swarm optimization (STPSO), Group statistical characteristics, Deregulated automatic generation control (AGC)

1 Introduction

Particle swarm optimization (PSO) is a population based stochastic search algorithm, proposed by Kennedy and Eberhart. Recently, the application of PSO has been growing in all areas of engineering because of its simplicity and ease of implementation. A basic PSO algorithm is developed based on social behavior of animals like bird flocking. PSO is randomly initialized. As the PSO algorithm progresses, the pbest variable stores local best value in the current iteration and the other variable gbest stores global best value up to the current iteration. The information stored in gbest and pbest makes the choice of population for next iteration more informed. In search of next population for the best result, the gbest variable tries to converge fast on global value and pbest of individual particles helps to move toward the best possible value.

In PSO, the trajectory of each particle is guided by the updated velocity based on gbest and pbest values, therefore a proper balance between them is needed. Such balance depends on some factors like acceleration constant and inertia weight of each particle. A selection of these parameters affects the performance of the algorithm. A large value of the inertia weight gives global search while a small value can provide local search [1].

The effectiveness of the algorithm depends on the strategy used to select population (for next iteration) on the basis of previous information (current iteration). In PSO, the variables (gbest and pbest) are affected by their neighborhood. Some time local optima in the earlier search space cannot be local optima in the existing search space due to the effects of neighborhood for choosing a variable value. This will trap PSO on local optima mainly for complex multidimensional problems.

To obtain desire response, tuning of proportional-integral (PI) or proportional-integral-differential (PID) controller is very important. Various control methodologies for instance auto-tuning and self-tuning are proposed. PID controller can be tuned by conventional methods like Ziegler–Nichols (Z–N) tuning, Cohen-Coon tuning and

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trial, and error methods, etc. Z–N method is suitable for online tuning including some trial and error which is not desirable. These tuning methods have some disadvantages: an excessive number of rules to set the gain, inadequate closed loop dynamic response and difficulties with nonlinear system [2]. Such problems are efficiently solved by the controller optimization using various soft computing techniques (fuzzy logic, genetic algorithm, and PSO, etc.).

Reference [3] compared the effectiveness of PSO based PID controller for load frequency control problem with Ziegler–Nichols based controller. The Z–N tuning method has advantages of large settling time, overshoot, rise time and steady state error compared with tuning by PSO controller. In [4], Z–N tuning method was compared with the fuzzy logic controller, the results showed that PID controller tuning by fuzzy logic have faster response than Z–N based tuned controller.

In the past few years, many researchers reported different variations in the PSO to solve the problems of convergence on the local best value [5]. Reference [1] proposed perturbed PSO based on the concept of perturbed global best in 2009. Reference [6] proposed PSO based restructure automatic generation control (AGC) system in 2010. Reference [7] introduced novel PSO with various adaptive inertia weights during the course of the run in 2011. Reference [8] used PSO with chaotic opposition based population initialization, called the CSPSO, to enhance performance of basic PSO for multidimensional problem. Reference [9] presented modified variants of PSO using different low discrepancy sequences. All these variations can help to carry out fast convergence, but still a multi-dimensional problem takes a large number of runs to reach an optimum value.

This paper utilizes some statistical parameters as a tracker to search global best value with less number of iterations. The application of statistically tracked PSO (STPSO) on AGC has given encouraging results. The AGC of power system uses a weighted linear combination of deviations in frequency and tie-line power flows, called the area control error (ACE), for simultaneous minimization of the system frequency deviation and tie-line power changes. In this paper, a newly developed STPSO method is used to obtain optimal gains of AGC controller.

The proposed paper has seven sections with an introduction. The next section is divided into two subsections: section 2.1 explains basic PSO and section 2.2 describes CPSO in brief. Section 3 introduces STPSO tracking system using different statistical parameters. The implementation of proposed STPSO is given in section 4. Section 5 describes system models for experimental studies. Numerical results of eleven benchmark functions and AGC system are presented in section 6 and section 7 concludes the paper outcome.

2 Overview of basic PSO

2.1 Basic PSO

PSO is one of the important evolutionary algorithms which are randomly initialized. The algorithm can search an optimum solution in a specified search space by updating the positions of particles. Each particle initializes positions and velocities using following equations:

$$X_j^k = X_{j,\min} + rand(n,d) \times (X_{j,\max} - X_{j,\min}) \tag{1}$$

$$v_j^k = v_{j,\min} + rand(n,d) \times (v_{j,\max} - v_{j,\min}) \tag{2}$$

where n is the number of population, d is the number of the optimize parameters, k is the current iteration count, $X_{j,\min}$ and $X_{j,\max}$ are the minimum and maximum values of j^{th} particles in search space, and $v_{j,\min}$ and $v_{j,\max}$ are the minimum and maximum values of the positions of j^{th} particles to move in search space [10].

The velocity and position of each (j^{th}) particle are updated using following equations:

$$v_j^{k+1} = wv_j^k + c_1 r_1 \left(pbest_j^k - x_j^k\right) + c_2 r_2 \left(gbest^k - x_j^k\right) \tag{3}$$

$$x_j^{k+1} = x_j^k + v_j^{k+1} \tag{4}$$

where r_1 and r_2 are two distinct random values between 0 and 1. The acceleration or constriction factors, c_1 and c_2, can move particles towards the best possible value ($gbest^k$) and w is the inertia weight used to balance between best and best values. The inertia weight change in succeeding iteration is described as [11, 12]:

$$w = w_{\max} - \frac{w_{\max} - w_{min}}{itermax} \times iter \tag{5}$$

where $iter$ is the iteration count, $itermax$ is the maximum number of iterations, and $w_{\max}$ and $w_{\min}$, are the upper and lower limits of inertia weights, respectively. Such inertia weight mechanism cannot successfully be used on modern complex multimodal problems [7, 13].

2.2 Chaotic PSO (CPSO)

CPSO uses chaotic sequences for inertia weight and constriction factor to obtain better diversity [14, 15].

To track gbest value corresponding to the best fitness value, inertia weight 'w' is updated dynamically using following expression:

$$w_j^k = w_{\min} + \frac{f_{\text{pbest}}^k |f_j^k - f_{\text{pbest}}^k|}{f_j^k |f_j^k - f_{\text{gbest}}^k|} \tag{6}$$

where w_j^k is the inertia weight of j^{th} population at k^{th} iteration, $w_{\min}$ is the minimum inertia weight, f_{pbest}^k is the fitness function correspond to pbest values at k^{th} iteration, f_j^k is the fitness functions of j^{th} population at k^{th} iteration, and f_{gbest}^k is the fitness function of gbest value at k^{th} iteration [16, 17 and 18].

Constriction factors c_1 and c_2 are highly depended on a fitness function corresponding to pbest and gbest values at k^{th} iteration. These factors are updated as:

$$c_{1j}^k = sqrt\left(\frac{f_j^k}{f_{\text{pbest}}^k}\right) \tag{7}$$

$$c_{2j}^k = sqrt\left(\frac{f_j^k}{f_{\text{gbest}}^k}\right) \tag{8}$$

The modified velocity up gradation in CPSO is given by:

$$v_j^{k+1} = w_j^k v_j^k + c_{1j}^k r_1 \left(pbest_j^k - x_j^k\right) + c_{2j}^k r_2 \left(gbest_j^k - x_j^k\right) \tag{9}$$

3 Development of STPSO: a new variant of PSO

Basic PSO works well with the simple optimization problem, but it can be trapped on local best value for some optimization problems. During execution of the proposed PSO algorithm, the convergence speed is enhanced by statistical particle parameters estimated during execution of the algorithm.

The proposed statistical tracked PSO uses following modified relation to update the velocity of particles:

$$v_{\text{new},j}^{k+1} = w v_j^k + c_1 r_1 \left(pbest_j^k - x_j^k\right) + c_2 r_2 \left(gbest^k - x_j^k\right) + \alpha^k \tag{10}$$

where α^k represents the acceleration factor based on one of the statistical parameter. The acceleration factor is computed based on two different statistical parameters, i.e., mean and median of the particle positions. The following expressions are used to compute acceleration factor.

$$\alpha^k = rand(X_{\text{gbest}}^k - X_{\text{s}}^k) \tag{11}$$

where X_{gbest}^k is the position corresponding to the global best value and X_{s}^k is one of the statistical parameters.

1) Median of particle position

$$X_{\text{s}}^k = \left(\frac{n+1}{2}\right)\text{th particle position} \tag{12}$$

2) Mean of particle position

$$X_{\text{s}}^k = \frac{\sum X_i}{n} \tag{13}$$

The position of the particle is updated as:

$$x_{\text{new},j}^{k+1} = x_j^k + v_{\text{new},j}^{k+1} \tag{14}$$

The STPSO using two statistical parameters is used for searching an optimum value with the improved diversity. First parameter is the mean value and the second one is the median value of the particle positions. The performance of PSO is enhanced by information obtained by statistical tracking based on mean and median values.

Now, fitness function value corresponding to $x_{\text{new},j}^{k+1}$ is calculated and compared with the fitness function value of x_j^k to generate a new population for the next iteration as:

$$x_j^{k+1} = \begin{cases} x_{\text{new},j}^{k+1} & \text{if } f(x_{\text{new},j}^{k+1}) \le f(x_j^k) \\ x_j^k & \text{if } f\left(x_j^k\right) < f(x_{\text{new},j}^k) \end{cases} \tag{15}$$

The following vector diagram (Fig. 1) shows the modification in position updating by the proposed method.

4 Implementation of proposed STPSO

Step 1: initialize the optimization parameters like population size (n), the number of maximum iteration (*itermax*), the number of variables (d), and the range of search space ($X_{\min}$ and $X_{\max}$), etc.
Step 2: set $k = 1$ and initialize particle position and velocities using (1) and (2), respectively.

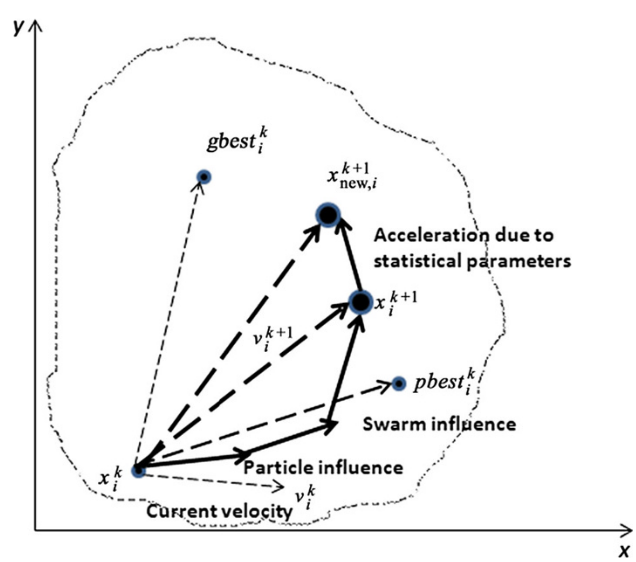


Fig. 1 Vector representation of position updating using STPSO

Step 3: calculate the fitness function of each population, and determine $pbest_j^k$ and $gbest^k$.
Step 4: update velocities of the particle (in (3)) and positions of particles (in (4)) and set $k = k + 1$.
Step 5: if $gbest^{k-1} - gbest^k < \varepsilon$, go to the next step, otherwise go to step 3 (where ε is a switch criteria to change tracking from basic PSO to mean).
Step 6: calculate the mean of particle position and determine the acceleration factor using (13) and update the velocities (using (10)) and the positions of particles using (14).
Step 7: calculate the fitness function of updated position and generate the particle positions for the next iteration (in (15)) and set $k = k + 1$.
Step 8: if $gbest^{k-1} - gbest^k < \varepsilon$, go to the next step, otherwise go to step 6 (where ε is a switch criteria to change tracking from mean to median).
Step 9: update velocity using median acceleration factor (in (12)) and generate particles for the next iteration (in (15)) and set $k = k + 1$.
Step 10: terminate the procedure if max iteration count reached or optimization problem converged on optimum values, i.e., mean or median position value becomes equal to the global value, otherwise go to step 7.

Implementation of the above algorithm is shown in Fig. 2.

5 System model

5.1 Implementation of distributed AGC problem

The proposed algorithm is tested on one of the important problems in power system which is the generation control in a distributed environment. AGC maintains system frequency and tie-line power flow at the scheduled level due to changes in load. Distributed AGC has many generation companies (Gencos) and distribution companies (Discos). Distribution companies have contracts to any distribution company within the area or to another area for transaction of power. An experiment for the present algorithm is done to find optimized gains of PID controller for four-area deregulated systems [19]. The combination of Gencos and Discos in the paper is shown in Fig. 3.

The block diagram of four area deregulated AGC system model is shown in Fig. 4. The detailed block diagram of areas-1, 2, 3 and 4 of the system is shown in Fig. 5. The scheduled tie-line power of four-area system is shown in Fig. 6. The test system parameter values of the test system are given in appendix.

In Fig. 5, the block of governor, turbine, reheater, and power system of i^{th} areas can be expressed by the transfer function model:

$$Governor_i = \frac{1}{1 + sT_{gi}} \tag{16}$$

$$Turbine_i = \frac{1}{1 + sT_{ti}} \tag{17}$$

$$Reheater_i = \frac{1 + sc_iT_{ri}}{1 + sT_{ri}} \tag{18}$$

$$Powersystem_i = \frac{K_{pi}}{1 + sT_{pi}} \tag{19}$$

where T_{gi}, T_{ti}, T_{ri}, and T_{pi} are the time constants of governor, turbine, reheater and power system of i^{th} area, respectively.

Figure 5 shows that a particular set of Gencos follows the load demanded by Discos. This information signal flows from a Discos to a particular Gencos corresponding to specified demand known as contract participation factor (*cpf*). The signal carries information as to which Gencos have to follow the load demanded by the Discos as:

$$cpf_{ij} = \frac{j^{\text{th}}\ \text{Disco power demand out of } i^{\text{th}}\ \text{Genco}}{j^{\text{th}}\ \text{Disco's total power demand}} \tag{20}$$

Inputs to the units 1–8 depend upon the *cpf* of four areas as shown in Fig. 5b. The corresponding ratio of area ratings is defined as:

$$\alpha_{ij} = \frac{\text{Rated power of } i^{\text{th}}\ \text{area}}{\text{Rated power of } j^{\text{th}}\ \text{area}} \tag{21}$$

The *cpf* and the area rating set the Discos participation matrix (DPM). In DPM, the number of columns is equal to the number of Discos and the number of rows is equal to number of Gencos. Each *cpf* in DPM is a fraction of a load contracted by Discos towards Gencos. The sum of all the entries in a column is unity.

The change in the load demand by Discos is reflected as a local load in the area to which this DISCOs belong. ACE signal is to be distributed among Gencos in proportion to their participation in the AGC known as "ACE participation factor (*apf*)". Area participation factors distribute ACE to n number of Gencos such that

$$\sum_{j=1}^{n} apf_j = 1$$

With the help of above DPM and *apf* matrix total generation required of individual Gencos can be calculated as:

$$\Delta P_{Gj} = \sum_j cpf_{ij} \Delta P_{\text{disco}\_j} + \sum_j apf_{ij} \Delta P_{\text{uncon}\_j} \tag{22}$$

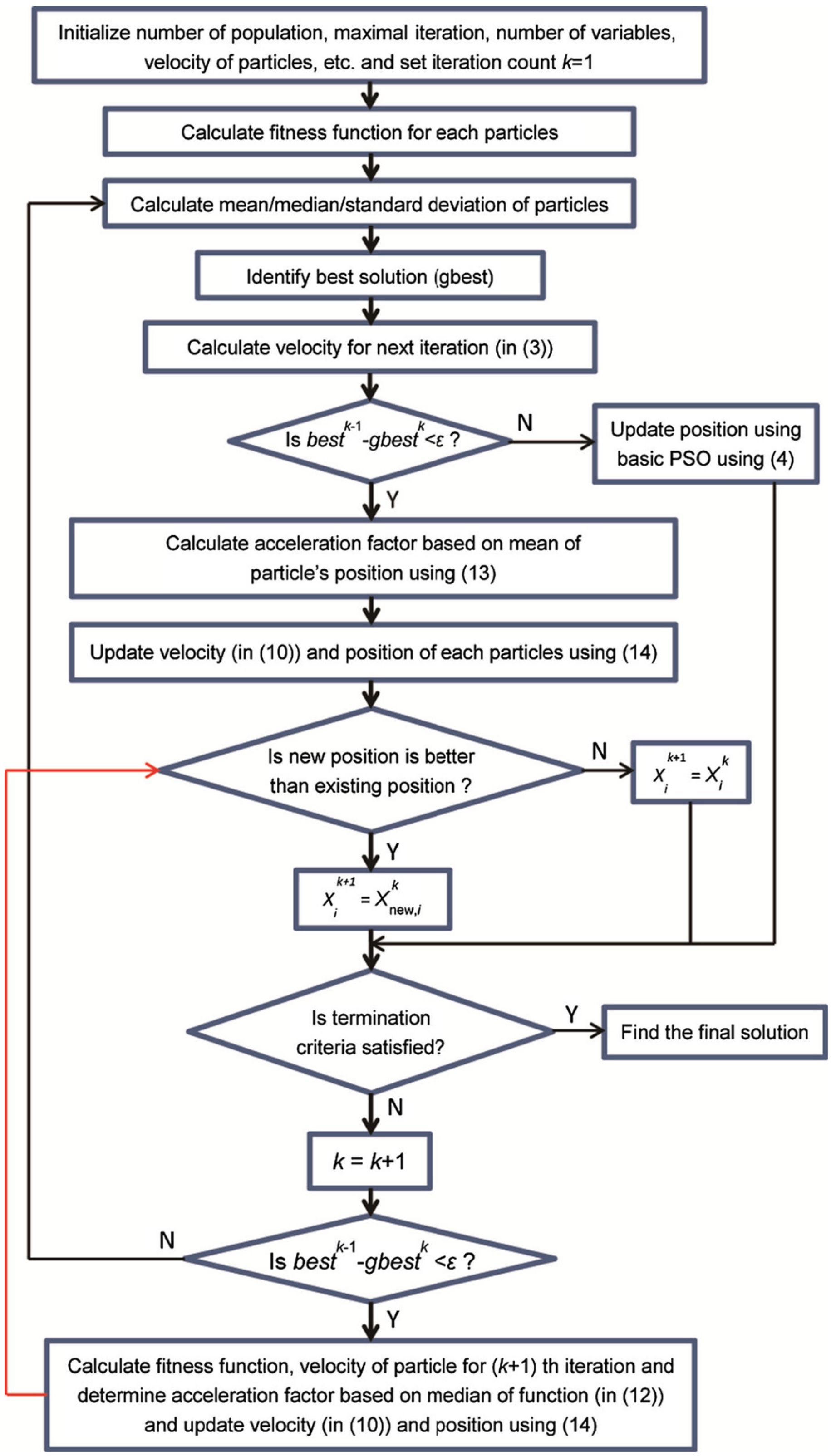


Fig. 2 Implementation of STPSO algorithm

where $\Delta P_{\mathrm{disco}\_j}$ is contracted schedule loads in DISCOs for four area system and $\Delta P_{\mathrm{uncon}\_j}$ is un-contracted local loads in area-1, 2, 3 and 4, which is reflected as a load disturbance.

The scheduled steady state power flow among areas can be represented by:

$$\begin{aligned}\Delta P_{\mathrm{tie},ij\mathrm{schduled}} = &(\text{demand of Disco in area-}j\\ &\text{from Genco in area-}i)\\ &-(\text{demand of Disco in area-}i\\ &\text{from Genco in area-}j)\end{aligned} \tag{23}$$

Hence, the tie-line power error is:

$$\Delta P_{\mathrm{tie},ij\,\mathrm{error}} = \Delta P_{\mathrm{tie},\,ij\,\mathrm{actual}} - \Delta P_{\mathrm{tie},ij\,\mathrm{scheduled}} \tag{24}$$

This scheduled steady state power flow among areas is shown in Fig. 6.

The tie-line power error signal is used to generate ACE signal as:

$$ACE_i = B_i \Delta f_i + \Delta P_{\mathrm{tie},ij\,\mathrm{error}} \tag{25}$$

where B_i is the frequency bias for i^{th} area and subscript i refers to the area ($i = 1,2,\ldots$).

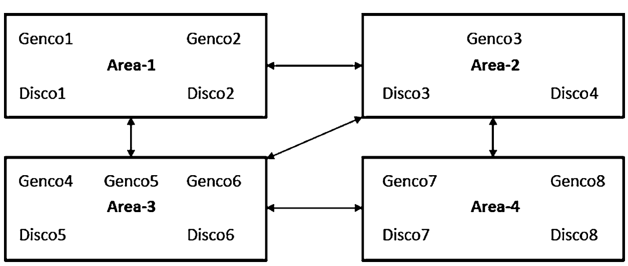


Fig. 3 Combination of Gencos-Discos for four-area AGC systems

The generalized equation for the change in frequency (ΔF) of i^{th} area can be evaluated using above equations and Figs. 4–6 as:

$$\begin{aligned}\Delta F_i = &\left\{\left[B_i \Delta F_i - \sum_{\substack{j=1\\ j\neq i}}^{n} \frac{T_{ij}}{s}\left(\Delta F_i - \Delta F_j\right)\right] PID_i - \frac{\Delta F_i}{R_i}\right\}\\ &\times\left[\frac{1 + s c_i T_{\mathrm{r}i}}{\left(1 + sT_{\mathrm{g}i}\right)\left(1 + sT_{\mathrm{t}i}\right)\left(1 + sT_{\mathrm{r}i}\right)}\right]\\ &\times\left[\sum_{\substack{j=1\\ j\neq i}}^{n} \frac{T_{ij}}{s}\left(\Delta F_i - \Delta F_j\right)\right]\left(\frac{K_{\mathrm{p}i}}{1 + sT_{\mathrm{p}i}}\right)\end{aligned} \tag{26}$$

where n is the number of areas connected to eight area through tie lines.

The state space model of the system shown in Fig. 4 can be expressed as [20]:

$$\dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \tag{27}$$

where $\boldsymbol{x} = [\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_4, \Delta P_{\mathrm{M1}}, \Delta P_{\mathrm{M2}}, \Delta P_{\mathrm{M3}}, \Delta P_{\mathrm{M4}}, \Delta P_{\mathrm{M5}}, \Delta P_{\mathrm{M6}}, \Delta P_{\mathrm{M7}}, \Delta P_{\mathrm{M8}}, \Delta P_{\mathrm{t1}}, \Delta P_{\mathrm{t2}}, \Delta P_{\mathrm{t3}}, \Delta P_{\mathrm{t4}}, \Delta P_{\mathrm{t5}}, \Delta P_{\mathrm{t6}}, \Delta P_{\mathrm{t7}}, \Delta P_{\mathrm{t8}}, \Delta P_{\mathrm{r1}}, \Delta P_{\mathrm{r2}}, \Delta P_{\mathrm{r3}}, \Delta P_{\mathrm{r4}}, \Delta P_{\mathrm{r5}}, \Delta P_{\mathrm{r6}}, \Delta P_{\mathrm{r7}}, \Delta P_{\mathrm{r8}}, s_{\mathrm{ACE1}}, s_{\mathrm{ACE2}}, s_{\mathrm{ACE3}}, s_{\mathrm{ACE4}}]^{\mathrm{T}}$ and $\boldsymbol{u}$ is the vector of power demands of Discos ($\boldsymbol{u} = [\Delta P_{\mathrm{L1}}, \Delta P_{\mathrm{L2}}, \Delta P_{\mathrm{L3}}, \Delta P_{\mathrm{L4}}]^{\mathrm{T}}$).

ΔP_{L} shown in Fig. 4 is referred as local load disturbance as:

$$\Delta P_{\mathrm{L1}} = \Delta P_{\mathrm{disco}\_1} + \Delta P_{\mathrm{disco}\_2} + \Delta P_{\mathrm{uncon}\_1} \tag{28}$$

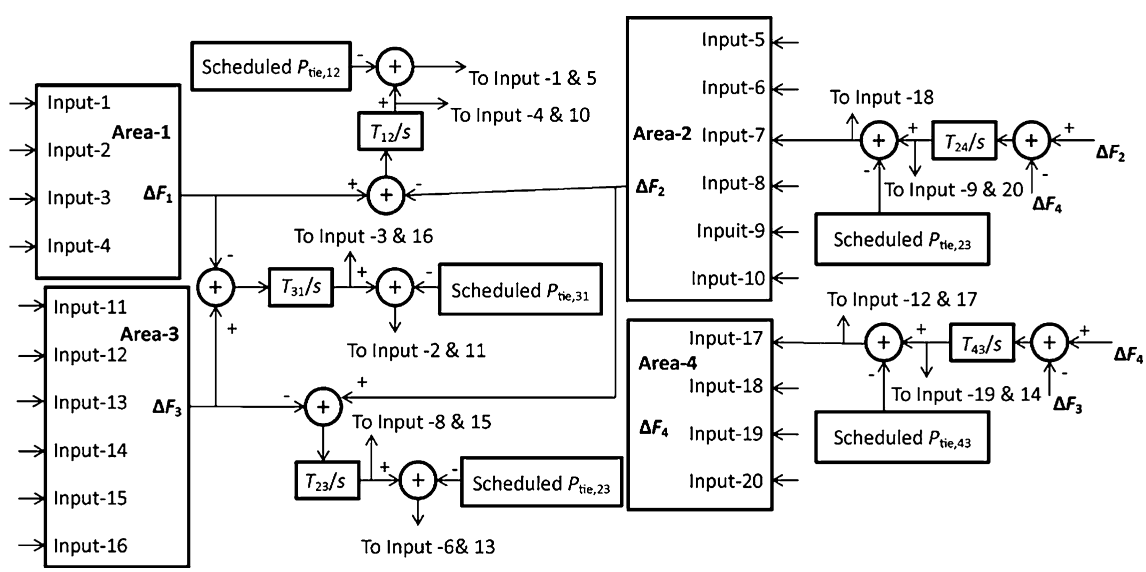


Fig. 4 Block diagram of four-area AGC systems

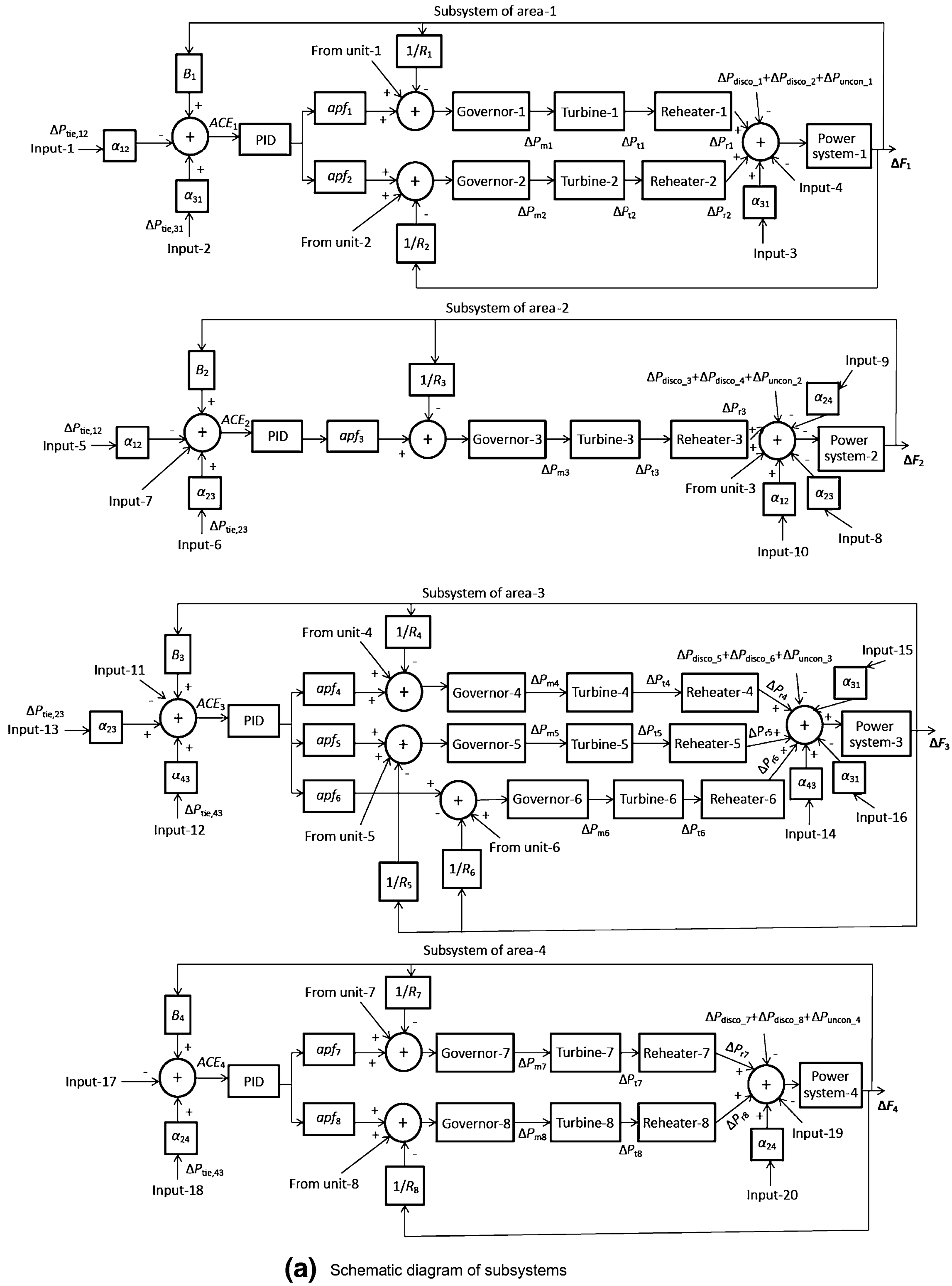
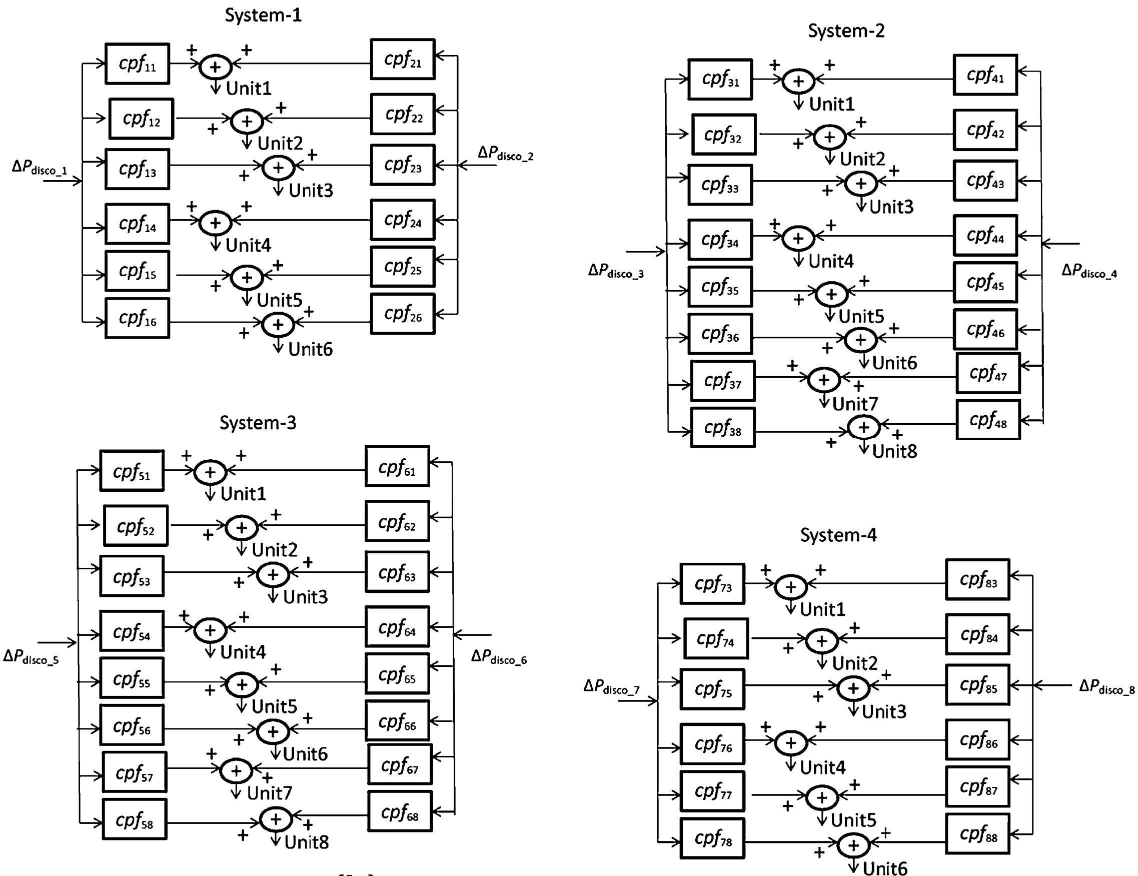


Fig. 5 Block diagrams of area-1, 2, 3 and 4 of systems



(b) Subsystem of systems 1, 2, 3 and 4

Fig. 5 continued

Similarly,

$$\Delta P_{\mathrm{L2}} = \Delta P_{\mathrm{disco\_3}} + \Delta P_{\mathrm{disco\_4}} + \Delta P_{\mathrm{uncon\_2}} \tag{29}$$

$$\Delta P_{\mathrm{L3}} = \Delta P_{\mathrm{disco\_5}} + \Delta P_{\mathrm{disco\_6}} + \Delta P_{\mathrm{uncon\_3}} \tag{30}$$

$$\Delta P_{\mathrm{L4}} = \Delta P_{\mathrm{disco\_7}} + \Delta P_{\mathrm{disco\_8}} + \Delta P_{\mathrm{uncon\_4}} \tag{31}$$

$\Delta P_{\mathrm{m}i}$ is the output of i^{th} governor. The expression for governor 1 is shown as:

$$\begin{aligned}\Delta P_{\mathrm{m1}} = {} & \left[\frac{(apf_1 B_1)\left(K_{\mathrm{p1}} + K_{\mathrm{d1}}\right)}{T_{\mathrm{g1}}} - \frac{1}{R_1 T_{\mathrm{g1}}}\right]\Delta F_1 \\ & + \frac{apf_1 \alpha_{31}\left(K_{\mathrm{p1}} + K_{\mathrm{d1}}\right)\Delta P_{\mathrm{tie,31}}}{T_{\mathrm{g1}}} \\ & + \frac{apf_1\left(K_{\mathrm{p1}} + K_{\mathrm{d1}}\right)\Delta P_{\mathrm{tie,12}}}{T_{\mathrm{g1}}} + \frac{1}{T_{\mathrm{g1}}}\end{aligned} \tag{32}$$

Similarly, the output of another governor is evaluated.

$\Delta P_{\mathrm{t}j}$ is the turbine output and is expressed in general form for j^{th} turbine as:

$$\Delta P_{\mathrm{t}j} = \frac{\Delta P_{\mathrm{m}j}}{T_{\mathrm{t}j}} - \frac{\Delta P_{\mathrm{t}j}}{T_{\mathrm{t}j}} \tag{33}$$

$\Delta P_{\mathrm{r}j}$ is the reheater output and is expressed in general form as:

$$\Delta P_{\mathrm{r}j} = \frac{\Delta P_{\mathrm{t}j}}{T_{\mathrm{r}j}} - \frac{\Delta P_{\mathrm{r}j}}{T_{\mathrm{r}j}} \tag{34}$$

The objectives of AGC problem are to obtain gain parameter and frequency bias so that minimum overshoot, minimum undershoot and minimum settling time are obtained. The present paper has used following optimization function to achieve the above goals [6, 16]:

$$\begin{aligned}F_{\min} = {} & 10 \times \sum_i (\lambda_0 - \lambda_i)^2 + 10 \times \sum_i (\xi_0 - \xi_i)^2 \\ & + 0.01 \times \sum_i \lambda_{i\mathrm{mag}}^2\end{aligned} \tag{35}$$

where $\lambda_0 = -1$, if $\lambda_i \geq 0$, λ_i is the real part of the i^{th} eigen value of matrix '$\boldsymbol{A}$' [6]. The relative stability is determined by λ_0. The damping ratio of the i^{th} eigen value is ξ_i and if imaginary part of the i^{th} eigen value is greater than 0.0 than set $\xi_0 = 0.2$ (minimum damping ratio). In the objective function the imaginary part of i^{th} eigen value λimag is considered if $\lambda_i \geq -1.0$.

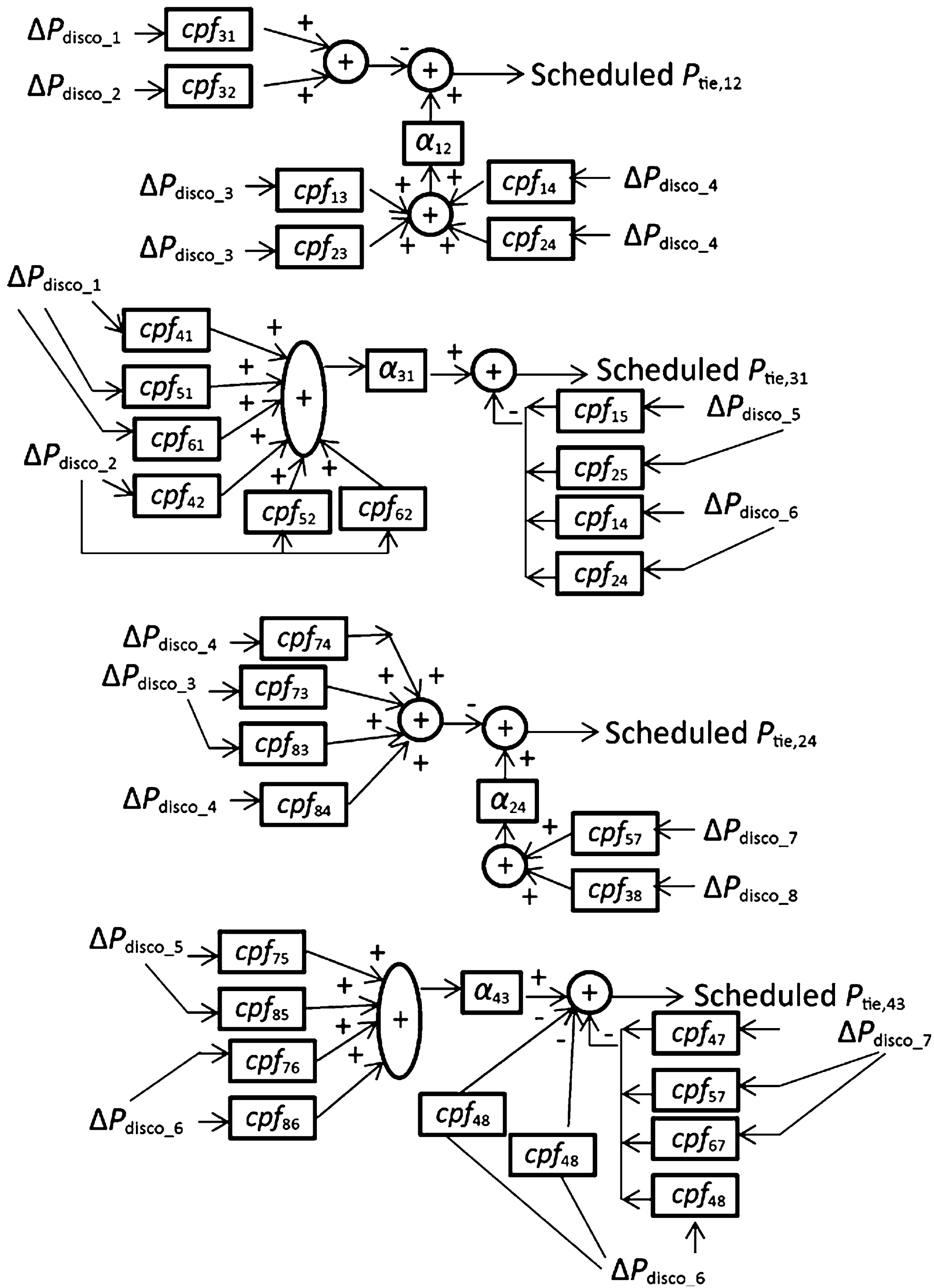


Fig. 6 Block diagram of scheduled tie-line power flow

6 Result and discussion

Four variants of PSO (basic PSO, chaotic PSO, PSO with median tracking, and PSO with mean and median tracking) are compared and tested for optimization of controller gains for four-area distributed AGC. The paper applied statistical (mean) tracking based on selected convergence criterion (ε). When mean tracking becomes slowly it switches to median tracking. STPSO has the following advantages.

1) Comparison based on statistical evaluation

Table 1 gives the comparative results for test functions. This table depicts that all statistical parameters like mean, median, standard deviation, standard error,

Table 1 Statistical comparison of deregulated AGC system with confidence level 0.95

Function design	Algorithm	Mean (fbest) in 100 runs (μ)	Median (fbest) in 100 runs	Std (fbest) in 100 runs (σ)	Best value (fbest) in 100 runs	Maximal value (fbest) in 100 runs	Frequency of convergence for 100 runs	Standard error of the mean fitness function (ε) = 2.0452 × σ/$\sqrt{n}$ n = 20 (pop size)	Confidence interval mean − ε ≤ μ ≥ mean + ε	Length of confidence 2 × 2.0452 × ε
Deregulated AGC system	PSO_basic	1500	1501.7	17.46	1487.5	1568.4	0	7.98506	1.50E03 ≤ μ ≥ 1.51E + 03	32.662
	CPSO	1500	1495.8	14.686	1479.4	1525.3	0	6.71641	1.49 + 03 ≤ μ ≥ 1.51E + 03	27.473
	PSO_mean	1480	14787	7.2178	1478.7	15043	31	3.30095	1.48E + 03 ≤ μ ≥ 1.49E + 03	13.502
	PSO_median	1500	1496	5.518	1483.3	1507.1	30	2.52357	1.49E + 03 ≤ μ ≥ 1.50E + 03	10.322
	PSO_mean and median	1478	1478	0	1478	1478	74	0	1.48E + 03 ≤ μ ≥ 1.48E + 03	0

confidence interval, and length of confidence have better values for PSO modified by statistical tracking compared with basic and chaotic PSO. Each function runs 100 times for population size 20 and statistical results are evaluated for 100 runs. As the dimension of functions increases, STPSO has found convergence speeds over other methods. Results show that PSO is trapped on local optimum value and poor performance for higher dimension order is given.

2) Convergence profile

Figure 7 represents the comparison of convergence for best fitness value with respect to the number of iterations. This figure shows that PSO with mean and median tracking search global values are very faster than the other methods for four-area deregulated AGC system.

3) Transient performance of AGC system

Figure 8 shows the dynamic responses of ACE and changes in area frequency with respect to time for four area deregulated AGC system. These responses show that PSO modified using mean and median tracking find optimum gains of PID controller ($K_p = 0.3014$, $K_i = 0.2665$, $K_d = 0.2038$) and reach a steady state value fast with minimum overshoot and settling time. The difference in minimum function values using basic (1487.5), chaotic (1479.4) and modification based on statistical parameters (1478) is listed in Table 1. The advantage of the proposed method for AGC system can be seen.

4) Schedule power

Figure 9 illustrates that optimization of controller by STPSO will rapidly set in schedule tie-line power among different areas on the scheduled value. Table 2 gives results of the scheduled generated power for four-area system. It shows that the error between the computed value and the calculated value is less than that of PSO modified by mean and median tracking system (approximately 0 for all Gencos).

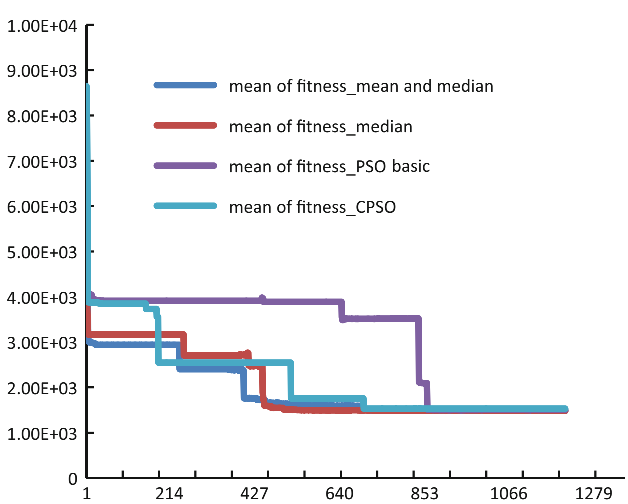


Fig. 7 Convergence for best fitness value with respect to iteration count for deregulated AGC system

7 Conclusion

A modified PSO algorithm is developed through introducing a statistical tracking with multiple strategies to search global best value. The proposed STPSO method is compared with existing optimization approaches, such as basic PSO and CPSO on AGC problems in power system. Experimental results for 100 runs show that the STPSO performs better under all conditions (i.e., various dimensionalities, number of variables, etc.) in terms of convergence rate and statistical parameters tabulated in Table 1. Numerical results indicate that the present strategy can effectively avoid the local optimum.

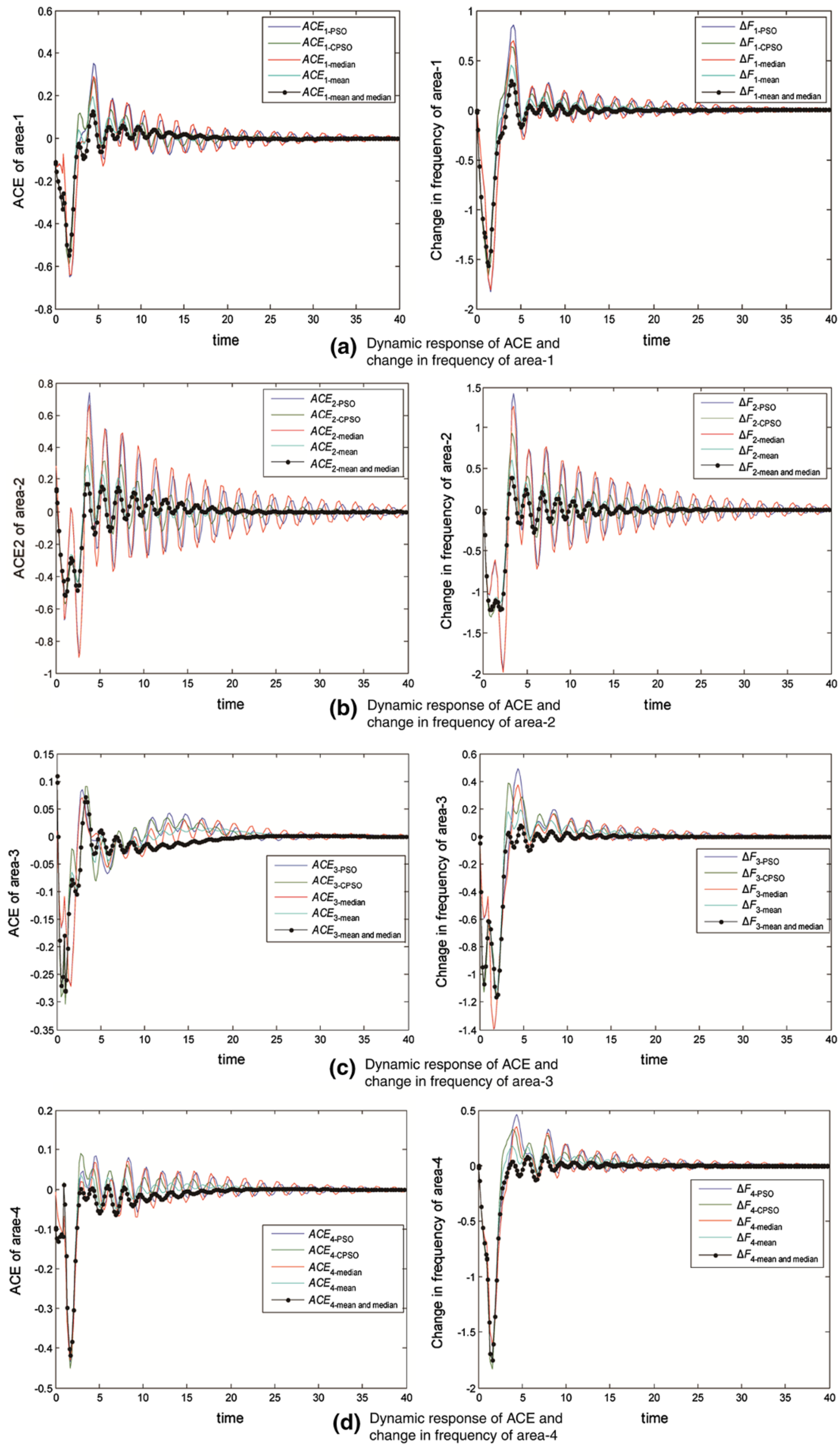


Fig. 8 Transient performance of four-area distributed AGC system

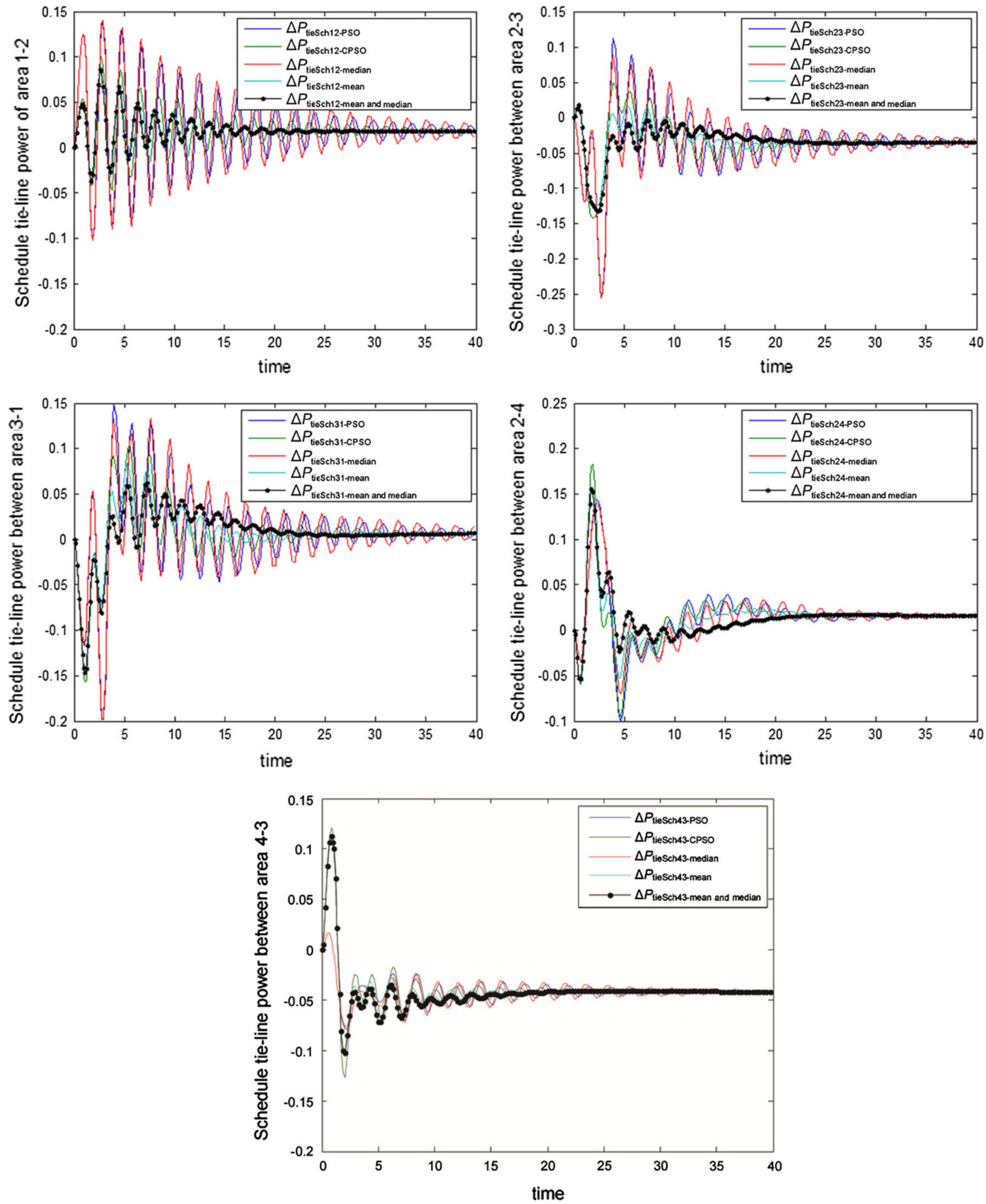


Fig.9 Transient performance of changes in schedule tie-line powers

Table 2 Steady state value of generated power of four-area system

Generating company	Algorithm	Computed values of GENCOs generation	GENCOs generation as obtained by algorithms	Error
Deltapg1	PSO	0.287	0.2872	0.000214
	CPSO		0.2869	0.0019
	PSO-median		0.2871	0.000145
	PSO-mean		0.2869	0.000012
	PSO mean and median		0.287	0
Deltapg2	PSO	0.3639	0.3632	0.000691
	CPSO		0.3629	0.001
	PSO-median		0.3631	0.000759
	PSO-mean		0.3634	0.000416
	PSO mean and median		0.363	0.0009
Deltapg3	PSO	0.575	0.5735	0.001484
	CPSO		0.5747	0.0017
	PSO-median		0.5733	0.001718
	PSO-mean		0.5748	0.000121
	PSO mean and median		0.575	0
Deltapg4	PSO	0.27833	0.3505	0.07217
	CPSO		0.3229	0.04448
	PSO-median		0.3506	0.07227
	PSO-mean		0.3229	0.044
	PSO mean and median		0.3228	0.04447
Deltapg5	PSO	0.27833	0.2839	0.00557
	CPSO		0.2562	0.02224
	PSO-median		0.2839	0.00557
	PSO-mean		0.2563	0.02203
	PSO mean and median		0.2561	0.02223
Deltapg6	PSO	0.27833	0.3039	0.02557
	CPSO		0.2763	0.02203
	PSO-median		0.3039	0.02557
	PSO-mean		0.2762	0.0007
	PSO mean and median		0.2761	0.00223
Deltapg7	PSO	0.29	0.2907	0.00069
	CPSO		0.2904	0.000418
	PSO-median		0.29	0
	PSO-mean		0.2899	0.000023
	PSO mean and median		0.29	0
Deltapg8	PSO	0.365	0.3657	0.000685
	CPSO		0.3651	0.0001
	PSO-median		0.3654	0.000418
	PSO-mean		0.36497	0.000027
	PSO mean and median		0.365	0

Appendix A

GENCOs participate in AGC as defined by $apf_1 = 0.5$, $apf_2 = 0.5$, $apf_3 = 1.0$, $apf_4 = 1/3$, $apf_5 = 1/3$, $apf_6 = 1/3$, $apf_7 = 0.5$, $apf_8 = 0.5$.

Nominal parameters of four-area test system are as follows.

$$B_1 = 0.25, B_2 = 0.25, B_3 = 0.25, B_4 = 0.25.$$

$$T_{g1} = 0.09, T_{g2} = 0.09, T_{g3} = 0.02, T_{g4} = 0.08, T_{g5} = 0.08, T_{g6} = 0.08, T_{g7} = 0.07, T_{g8} = 0.07.$$

$$T_{t1} = 0.5, T_{t2} = 0.5, T_{t3} = 0.4, T_{t4} = 0.3, T_{t5} = 0.3, T_{t6} = 0.3, T_{t7} = 0.4, T_{t8} = 0.4.$$

$$T_{r1} = 4.1, T_{r2} = 4.1, T_{r3} = 4.1, T_{r4} = 4.2, T_{r5} = 4.2, T_{r6} = 4.2, T_{r7} = 4.2, T_{r8} = 4.2.$$

$$T_{p1} = 20, T_{p2} = 20, T_{p3} = 20, T_{p4} = 20, T_{p5} = 20, T_{p6} = 20, T_{p7} = 20, T_{p8} = 20.$$

$$K_{p1} = 100, K_{p2} = 100, K_{p3} = 120, K_{p4} = 120, R_1 = 3.0, R_2 = 3.0, R_3 = 2.5, R_4 = 2.4, R_5 = 2.4, R_6 = 2.4, R_7 = 2.3, R_8 = 2.3.$$

Appendix B

Parameters for CPSO algorithm are as follows.

Initial population = 20.

Maximum iteration for benchmark function = 300 (for $D = 5$ and 10) and 400 (for $D = 20$).

Maximum iteration for AGC system = 1200.

$W_{min} = 0.1$

Parameters for PSO algorithm are as follows.

Initial population = 20.

Maximum iteration for benchmark function = 300 (for $D = 5$ and 10) and 400 (for $D = 20$).

Maximum iteration for AGC system = 1200.

$W_{max} = 0.6$, $W_{min} = 0.1$

$C_1 = C_2 = 1.5$.

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